Intelligence in Structural Health Monitoring of Composite Structures Using a Robust Signal Processing Protocol

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Abstract: This paper reports the development of a Structural Health Monitoring (SHM) system for a 2-D polymeric composite T-joint, used in maritime structures. The system developed relies on the examination of the strain distribution of the structure under operational loading and passing this data through a series of in-house developed pre-processing algorithms and eventually onto an Artificial Neural Network (ANN)-based inference engine. This system prompted the development of sophisticated pre-processing algorithms for the strain data. Improvements of 82% or more in detection accuracy were observed when these algorithms were invoked. Finite Element Analysis (FEA) was also conducted with delaminations of variable sizes at various locations in two structures, a composite beam and a T-joint. This paper focuses on a few normalization procedures that were developed to reduce the dependency of the algorithm on variables such as loading vectors. The work here also demonstrates the capability of the algorithm to detect and quantify instances when multiple damage zones are present.

Keywords: Structural Health Monitoring, Artificial Neural Networks, Delamination

1. Introduction

Glass fibre reinforced plastic (GFRP) laminates are widely used as structural materials due to their high strength to weight ratio and corrosion resistance. In military applications, composite structures also help to minimize electromagnetic radar signature for stealth operation [1]. The mode of failure of GFRP under static or dynamic loadings could be mainly due to matrix cracking or delaminations [2]. Delamination, being the more severe of the two, causes stiffness reduction and often leads to the catastrophic failure of the structure. Moreover, the detection of delamination is important to evaluate the reliability of GFRP laminates. Even invisible delaminations can severely degrade the mechanical properties and the load carrying capability of the structure. Damage initiates during service due to operational loading, aging, chemical attack, mechanical vibration and shocks. Existing techniques, such as X-ray, ultrasonic C-scan, and laser shearography [3] have been applied to detect these damages. However, it takes much time to inspect the GFRP laminate structures by these techniques, therefore, online detection [4] of the damage in these composite structures is desired.

This paper deals with one class of structural health monitoring techniques [5,6] which examines the strain distribution of the structure under normal operational loads. This strain measurement is then used to measure the structural integrity of the system. These methods revolve around the fact that damage in critical locations of a structure causes a significant change of the local strain distribution due to the changing load path. This characteristic is exploited as the working principle of the strain-based SHM system, especially for large and complex structures.

Artificial neural networks combined with pre-processing tools such the Damage Relativity Analysis Technique (DRAT) [7] have been used for damage diagnosis. This technique is capable of predicting the presence, the size and location of damage directly. The only shortcoming of this technique is that it is a model based technique, and the network has to be trained with a few different damage configurations prior to being used for prediction purposes.

However, with the development of pre-processing techniques such as the DRAT, the computational load and training time have also been reduced drastically. This paper indicates the efficacy of quantifying damage in GFRP T-joints using the ANN technique.

2. Artificial Neural Networks

Artificial neural networks [7, 8] (ANN) are large parallel distributed processors made up of simple processing units, called neurons, which have multiple interconnection paths. ANN's are capable of establishing mapping relationships between measurable but in-determinate features of structural damage and their physical parameters. Hence, for the classification and identification of structural damage, the only required task is to train the ANN in advance using a set of known damage features and their corresponding physical parameters. Multi-layer feed-forward back propagation network is the one that is most often used for performing functions such as data segmentation, compression and pattern recognition [9].

2.1 Network Architecture

The architecture of the network used to detect the presence, the location and the extent of damage, for the various damage configurations in a T-joint consisted of an input layer with eight sensory nodes (corresponding to the location of the strain sensors), three hidden layers with 8, 7 and 5 neurons respectively, and an output layer with 8 neurons (to predict the location and extent of damage). The resilient back propagation algorithm was used to train the network. In order to select the number of neurons in the hidden layers the 3- fold cross validation test was utilized.

2.2 Training Set

Optimised T-joint Finite Element Models were embedded with delaminations of different sizes and locations, and a pull-off load of 5kN at an angle of 0.55º (counter-clockwise to the y-axis) is applied to the bulkhead. A finite element analysis was then conducted and the strain observed at the sensor locations (Figure 1) is entered into a Damage Signature Database (DSD), corresponding to the location and size of the damage. The DSD was then compared with healthy strain signature from a T-joint experiencing a pull-off load of 5kN at an angle of 0.55° (counter-clockwise to the y-axis). The filtered DSD was then used to train the artificial neural network.

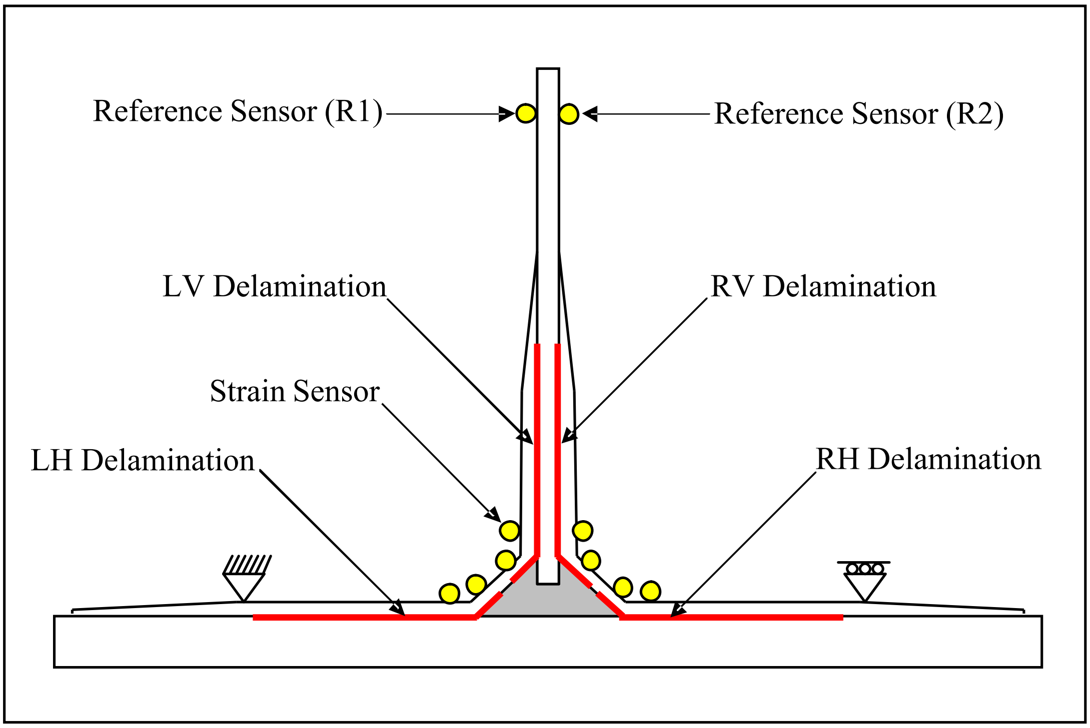
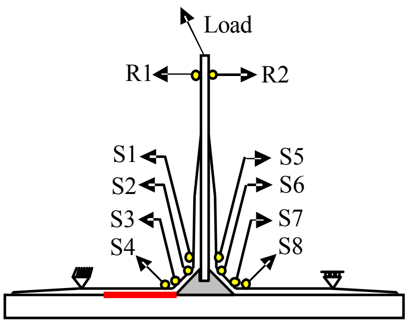
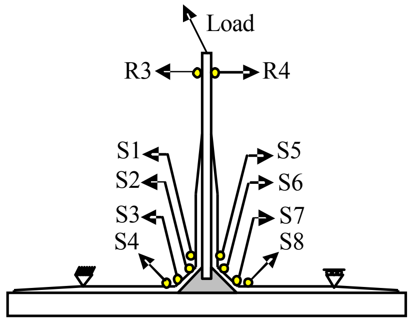


Figure 1 Sensor configurations for detecting multiple delaminations

3. DRAT Modification (MDRAT)

In order to remove the effect of the magnitude and the loading angle the DRAT algorithm had to be modified. Firstly, a database of strain signatures (undamaged) obtained from healthy T-joints loaded at a constant magnitude of 5kN, and variable loading angles were created as shown in Figure 2. These healthy T-joints consisted of the reference sensor R3 and R4, located corresponding to sensors R1 and R2. Next, the ratio $R_3/\{(\mathrm{Abs}(R_3)+\mathrm{Abs}(R_4)\}$ was calculated for all the cases in the healthy database.





Damage Signature Test Database

Test Case	(a)	(b)	(c)	(d)
Size	50 mm	75 mm	·	·
Location	LH	LH	·	·
Load	6000N	8000N	·	·
Load Angle	60deg	45deg	·	·
S1	-1.746	-1.449	·	·
S2	-3.239	-2.945	·	·
S3	-9.744	-10.358	·	·
S4	-9.889	-10.714	·	·
S5	13.968	15.292	·	·
S6	9.346	10.363	·	·
S7	3.935	4.744	·	·
S8	2.456	3.101	·	·
R1	*-2.148*	*-2.205*	·	·
R2	*2.484*	*2.838*	·	·
X_D → $\frac{R1}{\mathrm{Abs}(R1)+\mathrm{Abs}(R2)}$	-0.464	-0.437	·	·

Undamaged Strain Signature

Load	5000N	5000N	·	·
Load Angle	60 Deg	45 Deg	·	·
ε_1 → S1	-1.417	-0.899	·	·
ε_2 → S2	-2.829	-1.936	·	·
S3	-7.494	-5.971	·	·
S4	-8.256	-6.716	·	·
S5	11.717	9.617	·	·
S6	7.347	6.111	·	·
S7	2.991	2.697	·	·
S8	2.04	1.932	·	·
R3	*-1.79*	*-1.378*	·	·
ε_{10} → R4	*2.07*	*1.774*	·	·
X → $\frac{R3}{\mathrm{Abs}(R3)+\mathrm{Abs}(R4)}$	-0.464	-0.437	·	·

Create 10 polynomial equations by curve fitting, using $\boldsymbol{\varepsilon_i}$ & **X**.

Substitute $\mathbf{X_D}$ in all the ten polynomial equations to obtain the strain signature of the undamaged T-joint, experiencing load at the same loading angle as the current test case.

Compute R3/R1
The result was then factored into the strains present in the test case.

The processed damaged strain signature and the generated undamaged strain signature were then compared, and the unnecessary features were removed. The maximum absolute strain value in the filtered signature was identified and the strain signature was normalized with it. The normalized signature was then stored in a Test Database and consequently used as input data to the ANN for predicting the damage.

Figure 2 Schematic of the modification made to the DRAT algorithm to remove the effect of the load acting on the structure.

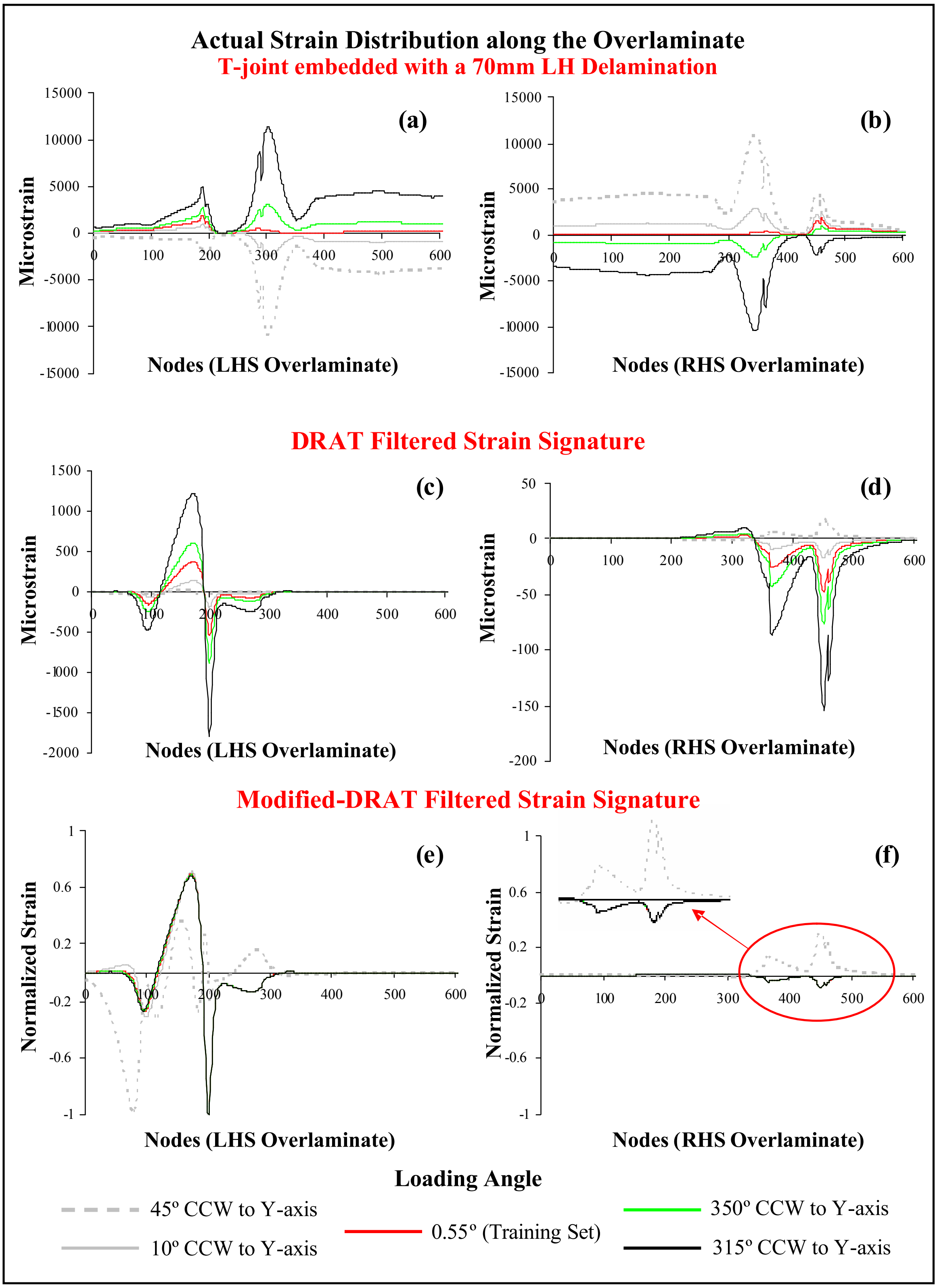


Figure 3 Comparison of the actual vs. the filtered strain signature for a T-joint embedded with a horizontal delamination subjected to different loading angles.

A polynomial curve fitting was then performed for strains obtained from every sensor location, for different loading angles. The polynomial equation is represented as:

$$y = a_0 + a_1 x + ... + a_k x^k \tag{1}$$

$$x = \frac{R_3}{Abs(R_3) + Abs(R_4)} \tag{2}$$

where,

$y = \varepsilon_i$ (ε is strain and i is the sensor number), a_k = coefficient of the polynomial, k = order of the polynomial.

A total of ten polynomial equations were created, i.e. for every sensor location. The polyfit function in Matlab® was then used to obtain the coefficients of the polynomial equations created. Due to the position of the reference sensors, the introduction of delaminations in T-joints has no effect on the ratio x. Hence, these polynomial equations were used to determine the healthy strain signature of a T-joint experiencing an identical loading pattern as the T-joint embedded with damage (test case).

A test set was then created, with T-joints embedded with delaminations in configurations which were not a part of the training set (i.e. different sizes, locations, loading magnitude and loading angle). The ratio $R_1/\{(\mathrm{Abs}(R_1)+\mathrm{Abs}(R_2)\}$ of the damaged strain signature, from the test case under investigation was then computed. This ratio was then substituted into all the ten polynomial equations created, to determine the strain signature of a healthy T-joint experiencing an identical loading pattern as the test case. The ratio of the R3 to R1 reference sensor strains, corresponding to the healthy structure and the damaged structure was then computed. The result obtained was factored with the damaged strain signature. The damaged strain signature was then compared with the estimated healthy strain signature, and the unnecessary features (stains associated with loading angle, magnitude and constraints) were removed to obtain a filtered strain signature. The maximum absolute strain value of the filtered strain signature was identified and it was used to normalize the strain signature. The normalized strain signature was then inserted into the Damage Signature Test Database (DSTD). This DSTD was then used to test the performance of the Artificial Neural Network. This normalization procedure is schematically represented in the case of composite T-Joint used in marine applications as seen in Figure 2 above.

In Figure 3 (e) & (f), it is clear that the modified-DRAT (MDRAT) algorithm has some effect in reducing the strain distribution near a delamination (when compared to Figures 3(a) and 3(b)) for the case of a 70mm damage in the horizontal configuration for the various load cases. A detailed description of this procedure as applied to T-joints has been given by Kesavan [10] and Kesavan *et al* [11]. In [11], the virtues of MDRAT were further implemented in another algorithm (Global Neural Network Architecture for Incorporating Sequential Processing of Internal Sub Networks - GNAISPIN) to further increase the robustness of the system. GNAISPIN uses multiple neural networks (virtually combined to one global network) to detect the presence of multiple delaminations in T-joints. Here, it is shown that when using MDRAT in conjunction with GNAISPIN, the accuracy of predicting the location and extent of damage can be increased to 94.5% for the cases tested [11].

4. Multiple Damage-site Detection

Using the test cases shown in Figure 1, the robustness of using MDRAT and GNASPIN was tested for multiple damage zones. In Table 1, the performance of these algorithms is shown for the correct detection of multiple damage zones. Also Table 1, it is seen that accuracies of the damage zone prediction of up to 98.8% and the least accurate prediction being 82.5% for 2 load cases. Here, 2 cases of 3 and 4 delaminations are tested with ANN-based algorithm. In the first case, the left vertical (LV), right Vertical (RV) and Right horizontal (RH) delaminations is tested. The second case test is one with 4 delaminations – left horizontal (LH), left vertical (LV), right vertical (RV) and right horizontal (RH).

5. Conclusions & Recommendations

In this paper, the performance of the structural health monitoring system in multiple damage scenarios is demonstrated regardless of loading vectors. The test set consisted of T-joints, subjected to variable loading magnitudes and variable loading angles, embedded with multiple delaminations of various sizes and damage configurations. The modified-DRAT and the GNAISPIN technique were used with the trained neural network to detect the number of delaminations, their location and extent of the delaminations. Twelve sensors (plus two reference sensors) were used to predict the damage. The

SHM system developed was found to be capable of predicting multiple delaminations, regardless of the loading magnitude and loading angle, with an average accuracy of 94.1%. This thus increases the prospects of deploying such an embedded intelligent system in real-world structures since it will be able to augment the information received from a finite and manageable array of structural sensors.

Table 1 Actual and predicted locations and sizes for 3 damage zones (LV-RV-RH) & 4 damage zones (LH-LV-RV-RH)

A - Actual Delamination Size   P- Predicted Delamination Size   N.E - Normalized Error %
N.E = Abs[(A-P)/(Max Delamination Size (100mm))]*100

Crack Configuration	Load	LH Delamination			LV Delamination			RV Delamination			RH Delamination		
		A	P	N.E	A	P	N.E	A	P	N.E	A	P	N.E
	N	mm	mm	%	mm	mm	%	mm	mm	%	mm	mm	%
LV-RV-RH	4000				90	105.5	**16**	90	107.5	**17.5**	58	55.7	**2.3**
	3250				35	31.3	**3.7**	40	47.8	**7.8**	60	57.6	**2.4**
LH-LV-RV-RH	5000	67	73.8	**6.8**	25	24.1	**0.9**	35	23.4	**11.6**	55	51.8	**3.2**
	6500	15	23.1	**8.1**	30	33.6	**3.6**	40	46.4	**6.4**	24	22.8	**1.2**

6. Acknowledgments

This work was conducted as part of a CRC-ACS research program. It was also partially supported by the United States Office of Naval Research, and their financial support is gratefully acknowledged. The authors thank Mr Terry Rosewarne, Mr Peter Tkatchyk, and Mr Sebastian Naselli from RMIT University.

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